Color Image Segmentation Using Hierarchical Merge Tree

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***Abstract*— Image Segmentation Using Hierarchical Merge Tree is analyzed in this paper by means of fast fuzzy c-means clustering algorithm and fuzzy membership function. Proposed work is done for the color segmentation, as previous research presents a connected coherence tree algorithm (CCTA) for image segmentation with no prior knowledge. It aims to find regions of semantic coherence based on the proposed ε-neighbor coherence segmentation criterion. RGB image is converted to Lab color space by taking average of each color component individually, then the average value of the color of small region selected is compared with all the pixels of the image and finally the desired object gets segmented efficiently. This algorithm runs in small time with much accuracy since, FFCM avoids some unnecessary comparisons between the pixels.**

Keywords*— *Image Segmentation, Clustering, Region-Based, RSST, Recursive Shortest-Spanning Tree, FFCM

I. INTRODUCTION

Image segmentation is critical for many computer vision and information retrieval systems, and has received significant attention from industry and academia over the last 30 years. Despite notable advances in the area, there is no standard technique for selecting a segmentation algorithm to use in a particular application, nor even is there an agreed upon means of comparing the performance of one method with another.

Like many complex computer vision problems, image segmentation is ill-defined. A common, if rather unconstrained, definition of segmentation is that it is the process of partitioning the set of pixels in an image into several disjoint subsets, according to a set of predefined criteria. Although this definition admits and conforms to almost all other definitions found in the literature, the criteria itself is usually a source of debate.

It defines image segmentation as the process of dividing an image into different regions such that each region is, but the union of any two adjacent regions is not, homogeneous. Similarly, Morris et. al.[9] describes segmentation as the process of partitioning an image into regions that are in some sense homogeneous, but different from neighboring regions. Skarbek and Koschan[13] for a simpler interpretation: the identification of homogeneous regions. All these definitions use the concept of homogeneity, which usually corresponds to identifying regions containing features that are relatively nearby according to a prescribed distance measure.

Segmentation may also be considered as an algorithmic attempt to mimic a human interpretation of an image, known as perceptual grouping. Considering segmentation in this way substantially increases the scope and complexity of the problem. Fu and Mui [21] and assume this viewpoint, stating that "the image segmentation problem is basically one of psychophysical perception, and therefore not susceptible to a purely analytical solution." It also implies this interpretation in their work on comparing automatic segmentation algorithms with human generated ground truth. It both argues that perceptual grouping is hierarchical in nature, and consequentially a flat partitioning of an image is insufficient for representing a perceptual segmentation.

Image segmentation is usually one of several components in a larger information processing system, and the variation observed in the definition of image segmentation is mirrored in the variation in requirements on the image segmentation algorithms in these systems. For multimedia information retrieval systems,[5] image segmentation algorithms capable of producing homogeneous regions usually suffice, since the purpose of image segmentation in such systems is often simply to create a set of localized features. Object recognition systems, on the other hand, usually require semantic objects from which features can be extracted and processed by pattern recognition engine (a support vector machine, for example).[7] In some cases, a priori information about the object is available, or can be fed back into the segmentation algorithm; in other cases, no such information is available, and the segmentation algorithm is required to produce regions or objects based on the image data alone.

II. THEORY

A. Hierarchical merge tree

First, Consider a graph, in which each node corresponds to a super pixel and an edge is defined between two nodes that share boundary pixels with each other. Starting with the primary over-segmentation so, finding a final segmentation, which is essentially the merging of initial super pixels, can be considered as combining nodes and removing edges between them. This super pixel merging can be done in an iterative fashion: each time pair of neighboring nodes is combined in the graph, and corresponding edges are updated. To represent the order of such merging, we use a full binary tree structure, that we call the hierarchical merge tree (or merge tree for

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short) throughout this paper. In a merge tree, node ∈ υ represents an image segment si ∈ 2 P, where d denotes the depth in Tree at which this node occurs. Leaf nodes correspond to initial super pixels in So. A non-leaf node corresponds to an image region formed by merging super pixels, and the root node corresponds to the whole image as one single region. An undirected edge eij ∈ E between nodes and its child exists when sj ⊂ si, and a local structure ({ $\upsilon_i^d, \upsilon_j^{d+1}, \upsilon_k^{d+1}$ }) represents si = sj ∪sk. In this way, finding final segmentation becomes finding a subset of nodes in Tree.

B. *Fuzzy membership function*

One of the key issues in all fuzzy sets is how to determine fuzzy membership functions. The membership function fully defines the fuzzy set. A membership function provides a measure of the degree of similarity of an element to a fuzzy the degree of similarity of an element to a fuzzy set. Membership functions can take any form, but there are some common examples that appear in real applications

- Membership functions can

Either be chosen by the user arbitrarily, based on the user's experience (MF chosen by two users could be different depending upon their experiences, perspectives, etc.)

Or be designed using machine learning methods (e.g., artificial neural networks, genetic algorithms, etc.) genetic algorithms, etc.)

- There are different shapes of membership functions; triangular, trapezoidal, functions; triangular, trapezoidal, piecewise-linear, Gaussian, bell-shaped, etc.

III. METHOD

In this paper, we present a hierarchical merge tree algorithm for color image segmentation. The three different ideas are incorporated in this algorithm to perform better segmentation. The input color image is first over-segmented into pixels. These pixels are grouped into some clusters according to the distance between the pixels. The clusters are formed using fast fuzzy c-mean clustering technique FFCM. Initially, centroids are fixed randomly between thee pixels of whole image at proper distance. The distance between each pixel to its nearest neighbour cluster center is calculated and the pixels with minimum distance are grouped into one cluster. Now, the average of the distance for each group is calculated new centroids are fixed. Again distance between pixels and centroids are calculated until no new centroid can be placed. The pixels of cluster are called members of the cluster with membership value lies between 0 and 1. For FFCM a threshold value is fixed between 0 and 1 and the distance calculation for the pixels whose membership values are less than T can be skipped. Each color present in the image are separated into R, G and B. The RGB image is converted to Lab color space. The RGB color space consists of all possible colors that can be made by the combination of red, green and blue light. It is a popular model in photography, television and computer graphics. Lab color space is defined by lightness and the color-opponent dimensions a and b. Lab is particularly notable for its use in delta-E calculations. When a small region is selected, the color difference (delta-E) in Lab color space is calculated for each pixel in the image between that pixel's color and the average of the Lab of selected region. All the pixels with color close to the average of selected region is then segmented from the whole image. After this process hierarchical merge tree algorithm is applied on converted image. This segmented image is passed through the mean filter for noise reduction.

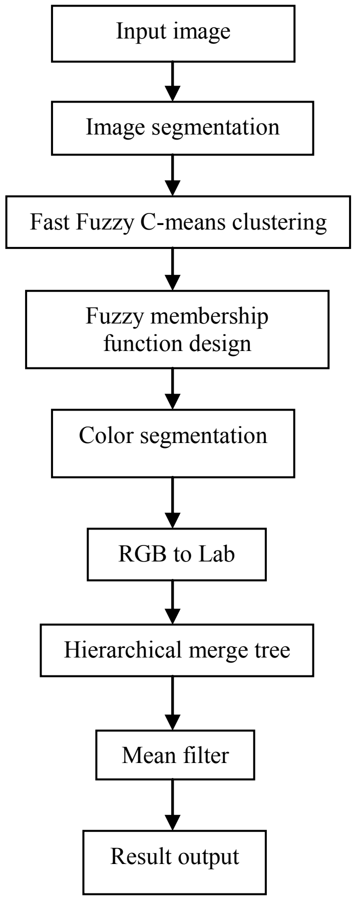

Fig.1 Flow of proposed method

A. *FAST FUZZY C-MEANS CLUSTERING*

This algorithm aims at decreasing the number of distance calculations of the FCM by computing the distances between data points and the nearest cluster centres. This is done to examine the points with membership values greater than a threshold, T, where the value of T is less than 1 and greater than 0.

In this case, there is no need to calculate distances for points with membership values less than T. since, these values do not severely affect the results and therefore, some distance calculations can be saved. The Fuzzy C-means Clustering (FCM) algorithm is a data clustering algorithm in which each data point belongs to a cluster to a degree specified by a membership grade. FCM partitions a collection of n data points x_i, i = 1, …, n into c fuzzy groups, and finds a cluster center in each group such that a cost function of dissimilarity measure is minimized. The major Proceedings of the 6th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering and Data Bases, Corfu Island, Greece, February 16-19, 2007 28 difference between FCM and hard clustering is that FCM employs fuzzy partitioning such that a given data point can belong to several groups with the degree of belongingness specified by the membership grades between 0 and 1. The membership matrix U is allowed to have elements with values between 0 and 1. However, imposing normalization stipulates that the summation of degrees of belongingness for a data set always be equal to unity:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1 \qquad (1)$$

The cost function (or objective function) for FCM is:

$$J(U, c_1, \ldots\ldots\ldots, c_c) = \sum_{i=1}^{c} j_i = \sum_{j}^{n} u_{ij}^{m}\, d_{ij}^{2} \qquad (2)$$

where u_{ij} uij is between 0 and 1; c_i is the cluster center of fuzzy group i; $d_{ij} = \| c_i - x_j \|$ is the Euclidean distance between i^{th} cluster and j^{th} data point; and m $\in[1,\infty)$ is weighting exponent.

The necessary conditions for Equation (2) to reach its minimum are:

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \qquad (3)$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \qquad (4)$$

The fuzzy C-means algorithm is simply an iterated procedure through the preceding two necessary conditions.

IV. RESULT

The proposed hierarchical merge tree algorithm is carried out on a color image. Segmentation of color image is done on the basis of color intensity values of the selected portion. The original color image consists of RGB components as in fig. 2

Fig. 2 original input image.

A small portion of image has been selected for segmentation.

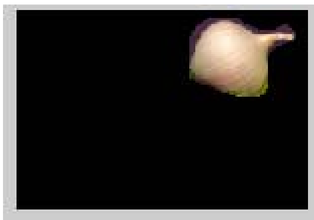

Fig. 3 crop the region from original image

Delta E calculation has been done for the converted Lab color space and the selected portion is shown in the form of gray image.

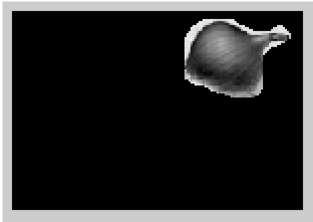

Fig.4 image masked region

Fig.5 dark image

Histogram of entire image and the masked region shows the number of pixels in intensity range.

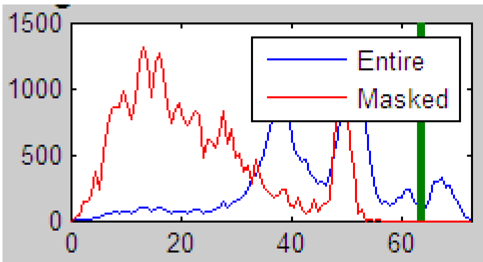

Fig.6 histograms of images

The color of selected portion is matched with the color of pixels in entire image, pixels having color close to the object's color masked.

Fig. 7 matching colors mask

Fig. 8 matching colors

Fig.9 non-matching colors

V. Comparison

The Existing Scheme, CCTA Works With Gray Image. It Segments the Image based on iteratively trains a new boundary classifier with accumulated samples for merge tree construction and merging probability prediction. It accumulates segmentation to generate contour maps. As proposed ε-neighbor coherence segmentation criterion. In this scheme, threshold value has to be changed for better segmentation. This method is slower because lots of calculation is needed to check whether the neighboring pixel belongs to the object of interest or outside the object. Whereas, the proposed method is applicable to color image. It is faster, efficient and easy to implement. This algorithm gives better result as the fuzzy clustering itself chooses the best possible value of threshold and segment the object accurately. The output of CCTA is not clear, it is affected by noise. Whereas, the proposed method first converts the color image to gray to segment it effectively. The output of our method is clear, only the selected part gets segmented without affected by noise. Since, we use mean filter to reject noise.

VI. Conclusion

We have proposed a modification of hierarchical merge tree model that iteratively trains a new boundary classifier with accumulated samples for merge tree construction and merging probability prediction. It accumulates segmentation to generate contour maps. As proposed work has been done for color segmentation by means of three different algorithms fast fuzzy c-means clustering algorithm, fuzzy membership function and Hierarchal merge tree. This gives efficient segmentation which is shown by the result of matching and non-matching colors.

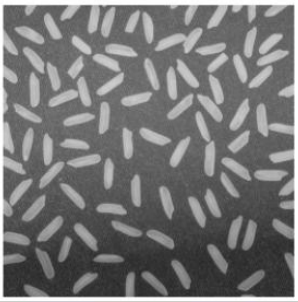

Fig.10 original gray image for proposed method

Fig.11 original color image for CCTA

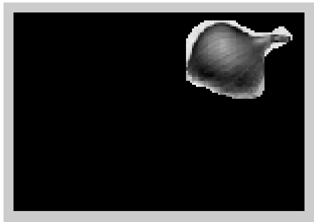

Fig.12 output of CCTA method

Fig.13output of proposed method

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